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Understanding truck co-driving behaviour using network analysis

Keywords: co-driving networks, infrastructure networks, network analysis, community detection, assortativity

Extended Abstract

Summary In recent years there have been several efforts that aimed to better understand social interactions with the help of network analysis [1]. In this work, build upon findings in [2], we examine a unique spatio-temporal dataset compromising more than 18 million measurements from license plate recognition systems situated at several highways. We try to relate what factors contribute to co-driving behaviour. The aim is to learn how trucks coordinate their behaviour. This is an important problem in the infrastructure domain, as optimized co-driving behaviour can help reduce traffic congestion and fuel usage.

Since multiple social mechanisms may exists for truck coordination, we look at different communities. In each community we determine what the most important social mechanism is. Our results indicate that in most communities truck drivers are more inclined to drive together with truck drivers from the same geographical area.

Network construction All trucks passing by at one of the 19 measurement locations in the Netherlands were recorded over a period of one year. From this raw data, we construct a co-driving network by considering all trucks as nodes that were driving together with another truck at least twice. A weighted edge is drawn in the network between co-driving trucks. For some nodes we have attributes available. This includes (a) spatial information (location of company and location of vehicle registration), (b) several features constructed from each time the truck was observed (number of locations observed, location where truck is most often observed) and (c) speed of truck. These attributes are used to understand which links are formed.

Approach To understand what factors contribute to link formation, we investigate node attribute assortativity. In our case, this metric measures the relation between node attributes and the presence or absence of links between nodes with similar attributes (for an exact definition, see e.g., [3]). The node attribute assortativity can be calculated for all the node attributes mentioned in the network construction section. Since several different social mechanisms may exists that relate to co-driving behaviour of trucks, we may expect to find different node attribute assortativities in different parts of the network. We partition the network in different communities using the Louvain modularity maximization algorithm [4]. For each community, we calculate for each attribute the node attribute assortativity. The attribute with the highest assortativity is the most likely explanation for the co-driving behaviour in that community.

Results We find that 2.6% of all measurements involves a co-driving activity. This results in a co-driving network of 85,391 nodes and 104,996 edges. The network shows properties which are often encountered in social and other real-world networks, such as (a) a large giant component, containing 65% of the nodes and 82% of the edges, (b) a relatively low average distance (8.1) and (c) a power law degree distribution. The degree and distance distribution are shown in Figure 1.

The network partitions in 120 communities. The modularity value for these partitions is 0.86, indicating that the network is highly modular and hence may have well defined communities. We find that attributes with spatial information are best able to explain the link formation process in 52 of the communities, whereas 38 communities were best explained by features derived from each time the truck was observed and 30 communities by the speed the trucks drove. It shows that truck drivers tend to co-drive with truck drivers from the same geographical area.

Moreover, the network shows a positive value for degree assortativity. This indicates that actively co-driving trucks preferentially connects to other active co-driving trucks.

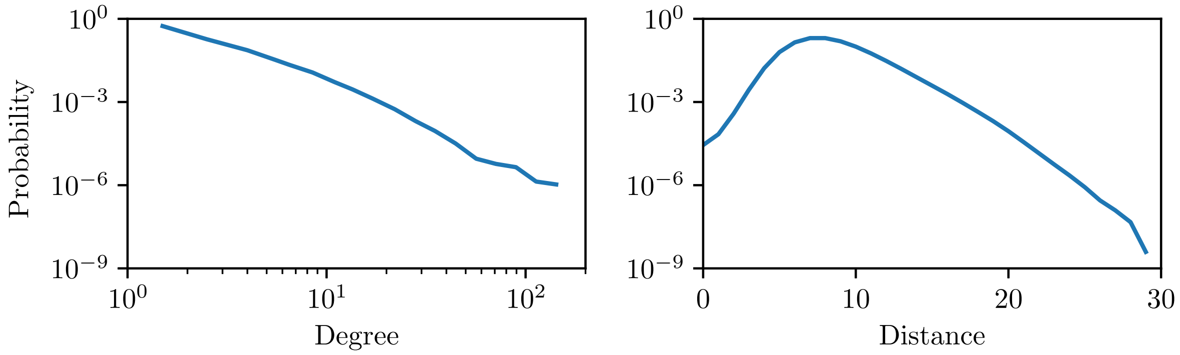

Figure 1: Degree and distance distribution of the co-driving network.

Future work Future work will focus on applying the knowledge observed from the network characteristics in the infrastructure domain. Additionally, we will extend our work to also incorporate dynamic aspects of the network. An improved understanding of dynamical social behavior may enable interventions that focus on spreading best practices amongst truck drivers. This can include improved fuel savings by coordinated co-driving.

References

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